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Title

The Impact of the ECB Monetary Policy on Systemic Risk Changes in Eurozone " BVAR framework"

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Abstract

Macroeconomic practitioners frequently work with multivariate time series models such as VARs, factor augmented VARs as well as time-varying parameter versions of these models (including variants with multivariate stochastic volatility). These models have a large number of parameters and, thus, over-parameterization problems may arise. Bayesian methods have become increasingly popular as a way of overcoming these problems.

In this paper, we discuss Bayesian vector autoregression (BVAR) in order to examine the impact of ECB's monetary policy decisions on the state of financial stability in Eurozone countries in the form of systemic risk in the banking sector. We argue that the environment of low interest rates encourages bank risk taking and increases systemic risk.

BVAR models are increasingly being used in modeling and forecasting macroeconomic variables in the recent years. When classical VAR model is extended with large number of endogenous variables to avoid omission bias the model estimation will suffer from curse of dimensionality and the result could be spurious. Estimation using Bayesian approach helps to overcome this problem by imposing shrinkage prior on the parameters to reduce parameter uncertainty, Further, Bayesian based simulation method such as *Gibbs sampling* easily estimates the uncertainties surrounding the point estimates of these models. This paper outlines a Markov Chain Monte Carlo (MCMC) algorithm that visits high posterior probability restrictions on the elements of both the VAR regression coefficients and the error variance matrix. Numerical simulations show that stochastic search based on this algorithm can be effective at both selecting a satisfactory model and improving forecasting performance, Gibbs sampler are used, For Gibbs sampler models I take a number of 'burn-in draws', so that I keep only the draws which have converged.

Keywords: *monetary policy, systemic risk, low interest rates,BVAR*

Introduction

The latest global financial crisis has put the mainstream view about monetary policy mechanisms of controlling interest rates to counteract financial exuberance (such as asset price bubbles) into question. Before the crisis, active interest rate regulation was considered a costly and inefficient measure (Bernanke and Gertler, 2001 or Gilchrist and Leahy, 2002), or in other words, central bank should intervene against market bubbles only to prevent price instability. Nowadays, the widely held belief that the current financial architecture is inherently fragile, and that widespread externalities stemming from some form of asset price corrections can have a systemic impact on the financial sector, disrupting financial intermediation and, in turn, jeopardizing the normal functioning of the real economy (Adrian et al., 2014). In theory, researchers argue that there is a new, so-called risk-taking channel of monetary policy through which low interest rates could lead to higher risk in the financial sector. Some studies (such as Allen and Gale, 2000) highlight the potential connection between central banks' monetary policy and the systemic risk present in the financial market. The standard monetary policy interacts with important drivers of financial imbalances, such as credit, liquidity and risk taking. Loose monetary policies drive up asset prices, which would eventually fall and cause financial instability. Moreover, extensive microeconomic evidence by Jiménez et al. (2014), based on the study of loan applications and contracts, demonstrate that low interest rates lead to increased bank risk taking.

In this brief paper, we aim to examine the effect of European Central Bank (ECB) monetary policy on the systemic risk present within the Eurozone's financial sector. This issue was recently addressed in the IMF study by Laseen et al. (2015) for the United States, for which a surprise in the tightening monetary policy does not necessarily reduce systemic risk, particularly when the state of the financial sector is fragile. Our paper extends the analysis of the impact of monetary policy on systemic risk changes to Eurozone countries and ECB policies. This is an important ex-post analysis aimed to answer the question about what drives the risk-taking channel, whether it was influenced solely by the volatility in the global financial markets or if the common monetary policy has also contributed. Our paper serves as a preliminary analysis of the systemic risk and monetary policy interconnectedness within the Eurozone, while contributing to the ever-going debate on, as formulated by White (2009), whether monetary policy should "lean or clean".

The objective of this paper is to study the existence of a *systemic* risk-taking channel (SRTC) in the Eurozone and how it behaves. Our contribution is original in four respects.

First, as risky activities and positions may spread from banks to the entire financial system, our focus is on *systemic* risk. In the empirical literature on the RTC, risk mainly refers to liquidity or default risk. Systemic risk is neglected, although according to the recent survey of Benoit et al. (2017), the mechanisms behind the RTC underlie an even more serious problem, which is systemic risk-taking. Benoit et al. (2017) define it as the fact that "*financial institutions choose*

to be exposed to similar risks and take large risk exposures, thus reinforcing amplification mechanisms, exposing themselves to default and their counterparts to contagion". As a source of systemic risk (along with contagion and amplification mechanisms), systemic risk-taking is an important concern for policymakers and academics. In this respect, a new generation of models with financial frictions proposed by Brunnermeier and Sannikov (2014), He and Krishnamurthy (2014) and Dewachter and Wouters (2014) demonstrate how low interest rates and low-risk environments are conducive to endogenous build-up of systemic risk. Thus, in this paper, we evaluate such a potential adverse effect of monetary policy on the indicator of Composite Indicator of Systemic Stress or simply named CISS (pronounced "KISS"). The main general goal of using stress indices such as the CISS is to measure the current state of instability, i.e. the current level of frictions, stresses and strains (or the absence of these) in the financial system and to condense that state of financial instability into a single statistic. The specific aim of the CISS is to emphasize the systemic nature of existing stresses in the financial system, where systemic stress is interpreted as an ex post measure of systemic risk, i.e. risk which has materialized already. The CISS permits not only the real time monitoring and assessment of the stress level in the whole financial system, but may also help delineating historical episodes of "financial crises" which might then be better compared and studied empirically in the context of early warning signal models, for instance. Last but not least, composite financial stress indicators can also be used to gauge the impact of policy measures directed towards mitigating systemic stress.

Second, in keeping with the previous point, we adopt a macroeconomic perspective. The majority of the empirical studies are performed on bank-level data. But evidence of risk-taking at the microeconomic level does not necessarily imply significant macroeconomic effects (Bonfim and Soares, 2014), *a fortiori* if, as asserted by Dell'Ariccia et al. (2017) , the economic magnitude of microeconomic effects is rather small. Moreover, while the literature mainly focuses on credit risk, policy rates may affect the overall balance sheet of economic agents, which in turn impact global risk, with uncertain macroeconomic and systemic effects. Yet, macroeconomic evidence on this matter is very scarce. We fill this gap by studying the existence of the SRTC at the euro area level using aggregate data on the monetary policy stance and the systemic risk.

Third, we search for evidence supporting the SRTC to know the impact of monetary policy on systemic risk. The RTC is usually gauged in the light of impulse response functions (IRFs) of risk measures to a one-period monetary policy shock.

The problematic of the thesis

The thesis attempts to answer the following research question:

What is the impact of monetary policy on systemic risk changes?

Methodology

To study the impact of ECB monetary policy on the European financial system stability, we employ the Bayesian vector autoregressive modeling framework (BVAR), consisting of six fundamental variables such as: Systemic risk "CISS",3 month Euribor interest rate "MEURIBOR", Index of Consumer Prices "ICP ", Money supply "M2", Industrial production index "INP", And Residential property price "RPP".

The structure of paper is as follows :After introduction section 2 focuses on providing a discussion of econometric model: VARs to develop some basic insights into the sorts of shrinkage priors (e.g. the Minnesota prior) and methods of finding empirically-sensible restrictions (e.g. stochastic search variable selection, or SSVS) that are used in empirical macroeconomics. Our goal is to extend these basic methods and priors used with VARs, to TVP variants; Section 3 outlines the data and provides an Empirical Illustration of Bayesian VAR Methods.

Chapter 1

Econometric Model Settings

Section 1: Bayesian VARs models

1.2 Introduction and Notation

The simple, reduced-form VAR model can be written as

$$\boldsymbol{Y_t = X_t A + \varepsilon_t} \text{ , with } \boldsymbol{\varepsilon_t} \sim \boldsymbol{N(0, \sum)} \qquad \textbf{(1)}$$

As we have shown in the previous subsection, this model can be written in the Form

$$\boldsymbol{y_t = (I_M \otimes X_t)\alpha + \varepsilon_t} \qquad \textbf{(2)}$$

Or compactly

$$\boldsymbol{y_t = Z_t \alpha + \varepsilon_t} \qquad \textbf{(3)}$$

Where $\alpha = vec(A)$.

In the computations presented henceforth, we will need the OLS estimates of α, A and $\sum$. Subsequently, using the notation $X = (X_1, \dots \dots X_T)'$, we define

$$\boldsymbol{\hat{\alpha} = (\sum Z_t' Z_t)^{-1} (\sum Z_t' y_t)} \qquad \textbf{(4)}$$

The OLS estimate of α

$$\boldsymbol{\hat{A} = (X'X)^{-1}(X'Y)} \qquad \textbf{(5)}$$

The OLS estimate of A

$$\boldsymbol{\hat{S} = (Y - X\hat{A})'(Y - X\hat{A})} \qquad \textbf{(6)}$$

The sum of squared errors of the VAR, and

$$\boldsymbol{\hat{\sum} = \hat{S} / (T - K)} \qquad \textbf{(7)}$$

The OLS estimate of $\sum$

Section 2: Priors

A variety of priors can be used with the VAR, of which we discuss some useful ones below. They differ in relation to three issues. First, VARs are not parsimonious models. They have a great many coefficients. For instance, α contains KMparameters which, for a VAR (6) involving 7dependent variables. Without prior information, it is hard to obtain precise estimates of so many coefficients and, thus, features such as impulse responses and forecasts will tend to be imprecisely estimated (i.e. posterior or predictive standard deviations can be large).For this reason, it can be desirable to "shrink" forecasts and prior information offers a sensible way of doing this shrinkage. The priors discussed below differ in the way they achieve this goal.

Second, the priors used with VARs differ in whether they lead to analytical results for the posterior and predictive densities or whether MCMC methods are required to carry out Bayesian inference. With the VAR, natural conjugate priors lead to analytical results, which can greatly reduce the computational burden. Particularly if one is carrying out a recursive forecasting exercise which requires repeated calculation of posterior and predictive distributions, non-conjugate priors that require MCMC methods can be very computationally demanding.

Third, the priors differ in how easily they can handle departures from the unrestricted VAR given in (1) such as allowing for different equations to have different explanatory variables, allowing for VAR coefficients to change over time, allowing for heteroskedastic structures for the errors of various sorts, etc. Natural conjugate priors typically do not lend themselves to such extensions.

2.1 The Diffuse Prior

The diffuse (or Jeffrey's') prior for α and $\sum$ takes the form

$$\boldsymbol{p(\alpha, \sum)} \propto /\sum/^{-(\boldsymbol{M+1})/\boldsymbol{2}}$$

The conditional posteriors are easily derived, and it is proven that they are of the form

$$\boldsymbol{\alpha/\sum, y} \backsim \boldsymbol{N(\hat{\alpha}, \sum)} \ , \ \boldsymbol{\sum/y} \backsim \boldsymbol{IW(\hat{S}, T-K)}$$

2.2 The Natural Conjugate Prior

The natural conjugate prior has the form

$$\alpha/\sum \sim ((\underline{\alpha}\ , \sum \otimes \underline{V}))$$

And

$$\sum^{-1} \sim \boldsymbol{W}(\underline{\boldsymbol{v}}, \underline{\boldsymbol{S}^{-1}})$$

The posterior for α is

$$\boldsymbol{\alpha}/\sum, \boldsymbol{y} \backsim \boldsymbol{N}(\bar{\boldsymbol{\alpha}}, \sum \otimes \bar{\boldsymbol{V}})$$

Where

$\bar{\boldsymbol{V}} = (\underline{\boldsymbol{V}}^{-1} + \boldsymbol{X}'\boldsymbol{X})^{-1}$ **And** $\bar{\boldsymbol{\alpha}} = \boldsymbol{vec}(\bar{\boldsymbol{A}})$ **with** $\bar{\boldsymbol{A}} = \bar{\boldsymbol{V}}\,(\underline{\boldsymbol{V}}^{-1}\underline{\boldsymbol{A}} + \boldsymbol{X}'\boldsymbol{X}\hat{\boldsymbol{A}})$

The posterior for $\sum$ is

$\sum^{-1} \big| \boldsymbol{y} \sim \boldsymbol{W}(\bar{\boldsymbol{v}}, \bar{\boldsymbol{S}}^{-1})$

Where

$\bar{\boldsymbol{v}} = \boldsymbol{T} + \underline{\boldsymbol{v}}$ And $\bar{\boldsymbol{S}} = \boldsymbol{S} + \underline{\boldsymbol{S}} + \hat{\boldsymbol{A}}'\boldsymbol{X}'\boldsymbol{X}\hat{\boldsymbol{A}} + \underline{\boldsymbol{A}}'\,\underline{\boldsymbol{V}^{-1}}\,\underline{\boldsymbol{A}} - \bar{\boldsymbol{A}}'(\underline{\boldsymbol{V}}^{-1} + \boldsymbol{X}'\boldsymbol{X})\bar{\boldsymbol{A}}$

2.3 The Minnesota Prior

The Minnesota Prior refers mainly to restricting the hyper parameters of α. The data-based restrictions are the ones presented in the monograph. The prior for α is still normal and the posteriors are the similar to the Natural conjugate prior case. $\sum$ is assumed known in this case (for example equal to $\hat{\sum}$).

2.4. Estimation of VARs using the Gibbs sampler

24.1 The Independent Normal-Wishart Prior-Posterior algorithms

We write the VAR as:

$$y_t = Z_t\beta + \varepsilon_t$$

where $Z_t = I_M \otimes X_t$ and $\varepsilon_t \sim N(0, \sum)$

It can be seen that the restricted VAR can be written as a Normal linear regression model with an error covariance matrix of a particular form. A very general prior for this model (which does not involve the restrictions inherent in the natural conjugate prior) is the independent Normal-Wishart prior:

$p(\beta, \sum^{-1}) = p(\beta)p(\sum^{-1})$

Where

$$\boldsymbol{\beta} \sim \boldsymbol{N}(\underline{\boldsymbol{\beta}}, \underline{\boldsymbol{V}_{\beta}}) \qquad \textbf{(8)}$$

and

$$\sum^{-1} \sim \boldsymbol{W}(\underline{\boldsymbol{v}}, \underline{\boldsymbol{S}^{-1}}) \qquad \textbf{(9)}$$

Note that this prior allows for the prior covariance matrix, $\underline{V_\beta}$, to be anything the researcher chooses, rather than the restrictive $\sum \otimes \underline{V}$ form of the natural conjugate prior. For instance, the researcher could choose a prior similar in spirit to the Minnesota prior, but allow for different forms of shrinkage in different equations. A noninformative prior can be obtained by setting

$$\underline{v} = \underline{S} = \underline{V_\beta^{-1}} = 0$$

The conditional posteriors are:
Posterior on $\beta = vec\ (B)$

$$\boldsymbol{\beta} \big| \boldsymbol{y}, \sum^{-1} \sim \boldsymbol{N}(\overline{\boldsymbol{\beta}}, \overline{\boldsymbol{V}_\beta}) \qquad \textbf{(10)}$$

Where $\overline{\beta} = \overline{V_\beta}\left(\underline{V_\beta^{-1}}\beta + \sum_{i=1}^{T} Z_t' \ \sum^{-1} y_t\right)$, and $\overline{V_\beta} = (\underline{V_\beta^{-1}} + \sum_{t=1}^{T} Z_t' \sum^{-1} Z_t)'$

Posterior on $\sum$

$$\sum^{-1} \big| \boldsymbol{y}, \boldsymbol{\beta} \ \sim \boldsymbol{W}(\overline{\boldsymbol{v}}, \overline{\boldsymbol{S}}^{-1}) \qquad \textbf{(11)}$$

Where $\overline{v}$=T+$\underline{v}$ and $\overline{S}$=$\underline{S}$+$\sum_{t=1}^{T}(y_t - Z_t\beta)(y_t - Z_t\beta)'$

The one-step ahead predictive density, conditional on the parameters of the model is:

$$y_t \big| Z_t, \beta, \sum \sim N(Z_t\beta, \sum)$$

In order to calculate reasonable predictions, Z_t, should contain lags of the dependent variables, and exogenous variables whichare observed at time $t-h$, where h the desired forecast horizon is. This result, along with a Gibbs sampler producing draws $\beta^{(r)}, \sum^{(r)}$ for $r = 1, \ldots \ldots \ldots, R$ allows for predictive inference[1]. For instance, the predictive mean (a popular point forecast) could be obtained as:

$$\boldsymbol{E}\left(\boldsymbol{y_t} \big| \boldsymbol{Z_t}\right) = \frac{\sum_{r=1}^{R} \boldsymbol{Z_t \beta^{(r)}}}{\boldsymbol{R}}$$

[1] Typically, some initial draws are discarded as the "burn in". Accordingly, r = 1;.....,R should be the post-burn in draws.

And other predictive moments can be calculated in a similar fashion. Alternatively, predictive simulation can be done at each Gibbs sampler draw, but this can be computationally demanding. For forecast horizons greater than one, the direct method can be used.
This strategy for doing predictive analysis.

2.4.2 Stochastic Search Variable Selection in VAR models

In the VAR model

$$\boldsymbol{Y_t = X_t A + \varepsilon_t} \qquad \textbf{(12)}$$

We can introduce the SSVS prior (George and McCullogh, 1993) which is a hierarchical prior of the form

$$\boldsymbol{\alpha | \gamma \sim N(0, D)} \qquad \textbf{(13)}$$

Where $\alpha = vec(A) = (\alpha_1, \dots \dots \dots \alpha_{KM})'$ and D is a diagonal matrix. If we write its $j - th$ diagonal element as D_{jj}, this prior implies that there is dependence on a hyperparameter $\gamma = (\gamma_1, \dots \dots \gamma_{KM})'$ of the following form

$$\boldsymbol{D_{j,j}} = \begin{cases} \boldsymbol{k_{0j}^2 \;\; if\ \gamma_j = 0} \\ \boldsymbol{k_{1j}^2 \;\; if\ \gamma_j = 1} \end{cases} \qquad \textbf{(14)}$$

Where we a-priori set the hyperparameters $k_{0j}^2 \to 0$ and $k_{1j}^2 \to \infty$.This prior implies that when $\gamma_j = 0$ the prior variance of the $j - th$ element of α, call it α_j, will be equal tok_{0j}^2, which is very low since$k_{0j}^2 \to 0$. Subsequently, the posterior of the $j - th$ parameter will be restricted in this case to shrink towards the prior mean, which is 0. In the alternative case, $\gamma_j = 0$, the restriction will remain unrestricted and the posterior will be determined mainly by the likelihood. The SSVS prior in (13) can be written in a mixture of Normal form, which is more illuminating about the effect of each $\gamma_j$on the prior ofα_j:

$$\boldsymbol{\alpha_j | \gamma_j \sim (1 - \gamma_j) N(0, k_{0j}^2) + \gamma_j N(0, k_{1j}^2)}$$

The way in which it is determined whether γ_j is 0 or 1 (and hence whether α_j is restricted or not) is not chosen by the researcher, as in the case of the Minnesota prior which favors only own lags and the constant parameters (and restricts the other R.H.S. variables in a semi-data-

based way). The value of γ_j should is determined fully in a data-based fashion, and hence a prior is assigned to . In a Bayesian context, a prior on a binomial variable which results in easy computations is the Bernoulli density. Note also that it helps calculations if we assume that the elements of are independent of each other and sample each γ_j individually. Subsequently, the prior for is of the form

$$\boldsymbol{\gamma_j} \,|\, \boldsymbol{\gamma_{\backslash -j}} \sim \boldsymbol{Bernouli}\,(\mathbf{1}, \underline{\boldsymbol{q_j}})$$

This prior can also be written in the form: $\Pr(\gamma_j = 1) = \underline{q_j}$ and $\Pr(\gamma_j = 0) = 1 - \underline{q_j}$
A typical "noninformative" value of the hyperparameter $\underline{q_j}$ is 0.5, although the reader might want to consult Chipman et al. (2001) and George and McCullogh (1997) on this issue. Finally for $\sum$ we assume the standard Wishart prior

$\sum^{-1}, \sim W(\underline{v}, \underline{S}^{-1})$

The conditional posteriors are

1. Sample α from the density

$$\alpha | y, \gamma, \Sigma \sim N(\overline{\alpha}_\alpha, \overline{V}_\alpha),$$

Where $\overline{V}_\alpha = [\sum^{-1} \otimes (X'X) + (DD)^{-1}]^{-1}$ And $\overline{\alpha}_\alpha = \overline{V}_\alpha\,[(\,\psi\psi'\,) \otimes (X'X)\hat{\alpha}$ is the OLS estimate of α

2. Sample γ_j from the density

$$\boldsymbol{\gamma_j} \,|\, \boldsymbol{\gamma_{-j}}, \boldsymbol{b}, \boldsymbol{y}, \boldsymbol{Z} \sim \boldsymbol{Bernouli}(\mathbf{1}, \overline{\boldsymbol{q}}_{\boldsymbol{j}}) \qquad \textbf{(15)}$$

Where

$$\overline{\boldsymbol{q}}_{\boldsymbol{j}} = \frac{\frac{\mathbf{1}}{\boldsymbol{k_{1j}}}\mathbf{exp}\left(-\frac{\alpha_j^2}{2{k_{1j}}^2}\right)\underline{\boldsymbol{q_j}}}{\frac{\mathbf{1}}{\boldsymbol{k_{1j}}}\mathbf{exp}\left(-\frac{\alpha_j^2}{2{k_{1j}}^2}\right)\overline{\boldsymbol{q}}_{\boldsymbol{j}} + \frac{\mathbf{1}}{\boldsymbol{k_{0j}}}\mathbf{exp}\left(-\frac{\alpha_j^2}{2{k_{0j}}^2}\right)(\mathbf{1} - \underline{\boldsymbol{q_j}})}$$

3. Sample $\sum^{-1}$from the density

$\sum^{-1} \sim Wishart(\overline{v}, \overline{S})$

- Where $\overline{v} = T + \overline{v}$ And $\overline{S} = (\underline{S}^{-1} + \sum_{t=1}^{T}(Y_t - Z_t\,\theta)'(Y_t - Z_t\theta)^{-1}$

2.4.3 Flexible Variable Selection in VAR models

Another way to incorporate variable selection in the VAR model is to explicitly restrict the parameter to be zero, when the indicator variable is zero. The VAR model

$$\boldsymbol{y_t = Z_t\beta + \varepsilon_t}$$

Can be written now as

$$y_t = Z_t\theta + \varepsilon_t$$

Where $\theta = \Gamma\beta$ and $\Gamma = diag(\gamma)$=$diag(\gamma_1, \dots\dots, \gamma_{KM})$.

If we denote by γ_j the j-th element of the vector γ (which is also the j-th diagonal element of the matrix), and by $\gamma_{\backslash j}$ the vector where the j-th element is removed, a Gibbs sampler for This model takes the following form:

Priors:

$$|\beta \sim N_{MK}(\underline{\beta}, \underline{V}) \quad (16)$$

$$\gamma_j|\gamma_{\backslash -j} \sim Bernoulli(1, \underline{\pi}) \quad (17)$$

$$\Sigma^{-1} \sim Wishart(\underline{v}, \underline{S}) \quad (18)$$

Conditional posteriors:

1. Sample α from the density

$$\boldsymbol{\beta \,|\, \gamma, H, y, Z \sim N_{MK}(\overline{\beta}, \overline{V})} \quad \textbf{(19)}$$

Where

$\overline{V} = (\underline{V}^{-1} + \sum_{t=1}^{T} Z_t^{*\prime} \Sigma^{-1} Z_t^*))^{-1}$ and $\overline{\beta} = \overline{V}(\underline{V}^{-1}\underline{\beta} + \sum_{t=1}^{T} Z_t^{*\prime} \Sigma^{-1} Y_t)$,

and $Z_t^* = Z_t\Gamma$

2. Sample γ_j from the density

$$\boldsymbol{\gamma_j \,|\, \gamma_{-j}, b, y, Z \sim Bernouli(1, \overline{\pi}_j)} \quad \textbf{(20)}$$

Preferably in random order j,where $\boldsymbol{\overline{\pi}_j = \frac{l_{0j}}{l_{0j} + l_{1j}}}$ **,and**

$$\boldsymbol{l_{0j} = exp(-\frac{1}{2} tr\left(\sum_{t=1}^{T}(Y_t - Z_t\theta^*\right)'\sum^{-1}(Y_t - Z_t\theta^*))\pi_{0j}}$$

$$\boldsymbol{l_{0j} = exp(-\frac{1}{2} tr\left(\sum_{t=1}^{T}(Y_t - Z_t\theta^{**}\right)'\sum^{-1}(Y_t - Z_t\theta^{**}))(1 - \pi_{0j})}$$

Here we define θ^* to be equal to θ but with the j - th element θ_j=β_j(i.e. when $\gamma_j = 1$). Similarly, we define $\theta^{**}$to be equal to θ but with the j - th element $\theta_j = 0(i.e. when\, \gamma_j = 0)$

3. Sample $\sum^{-1}$ *from the density*

$$\boldsymbol{\sum^{-1} \sim Wishart(\overline{v}, \overline{S})}$$

Where $\overline{v} = T + \underline{v}$ and $\bar{S} = (\underline{S^{-1}} + \left(\sum_{t=1}^{T}(Y_t - Z_t\theta\right)'(Y_t - Z_t\theta))^{-1}$

Chapter 2

Empirical Illustration

Section 1: DATA description

We apply the methodology described in the previous section to Eurozone; we obtain historical data on macroeconomic variables from the ECB Statistical Data Warehouse.

We use monthly data and use aggregate indicators for the whole Eurozone. Our sample ranges from January, 2000 to March 2018 and contains 219 observations.

The composite indicator of systemic stress for Eurozone is depicted in **Figure 1**. We can clearly see the build-up phase shortly since 2004, while reaching its peak during volatile in beginning of 2008 and 2009. After the beginning of the Eurozone sovereign debt crisis, in the end of 2009, the level of systemic instability increased (especially after intensified concerns during few first months of 2010) and it started to fall only after ECB offered free and unlimited support for all Eurozone countries involved in a sovereign state bailout/precautionary program from European Financial Stability Facility on September 6, 2012.

The Used macroeconomic variables are represented in **Figure 2**

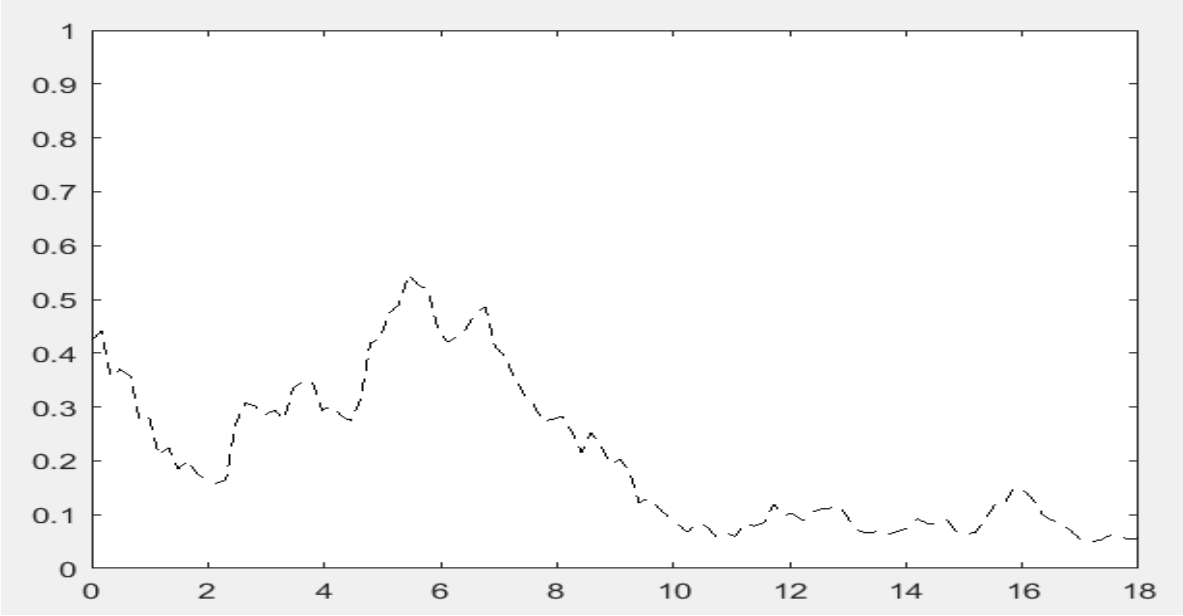
For the purposes of our study, changes in the ECB monetary policy are interpreted as shocks. From examining the changes in the 3M-EURIBOR, we can easily identify the mostly unvarying phase prior to the financial crisis from the 3rd quarter of 2002 to the 3rd quarter of 2005, when the official ECB interest rates remained quite low. This loose monetary policy fed the risk-taking behavior of economic agents, so when it stopped, the market was just a short step from collapsing. The collapse came in the 3rd quarter of 2008, when the banking sector failed to overcome the US sub-prime mortgage crisis. The Federal Reserve and ECB coordinated reaction was to lower the interest rate at impact in order to stop the up-coming recession. After seven years, the interest rates are still at near-zero values and now longer available to ECB to use as a monetary policy tool in the situation, when the inflation is extremely low (see the Harmonized Index of Consumer Prices - HICP). Since the 2% inflation rate was generally considered the natural display of growing economies, the European Central Bank seems to manage its primary goal of price stability without any difficulties until the crisis. The prolonged crisis period brought deflationary fears and pressures within the Eurozone. The loose monetary policy before the crises also explains the growing money supply in the Eurozone countries (represented by M2 aggregate), where the multiplicative money effect was feeding the economic growth. The money supply declined significantly during the crisis. The recent levels of money supply are influenced by quantitative easing programs.

The Real property price represents the real estate. developments in real estate markets have been significant drivers of the evolution of the financial system, in the case of Housing Market crisis (in which a crisis is defined as a real house price drop of at least 10% over one year), the effect of the benchmark ratio on systemic risk intensity operates entirely through the positive coefficient of the interaction between the bank-market ratio and the crisis dummy.

Developments in the residential real estate sector can have significant implications for financial stability and the real economy**.** Residential real estate (RRE) represents a major part of households' wealth and constitutes a major source of collateral for lenders. Moreover, mortgages often make up large parts of banks' balance sheets, and are the largest and most common form of debt among households. Furthermore, housing construction is typically an important component of the real economy, as a source of employment, investment and growth. Experiences show that systemic risk relating to RRE – stemming from excessive risk-taking, high leverage, misaligned incentives and boom/bust tendencies, etc. – may lead to significant risks to domestic financial stability and serious negative consequences for the real economy, as well as potentially leading to negative spillovers to other countries. Vulnerabilities in RRE may manifest themselves through direct effects – through losses of capital or funding among lenders – and indirect effects in terms of foregone economic output, which may have second-round effects on the financial system. The underlying sources of such vulnerabilities differ. However, they often emerge from domestic structural features, from social and economic policies (e.g. tax deductibility of mortgage interest payments), from cyclical developments, or combinations thereof.

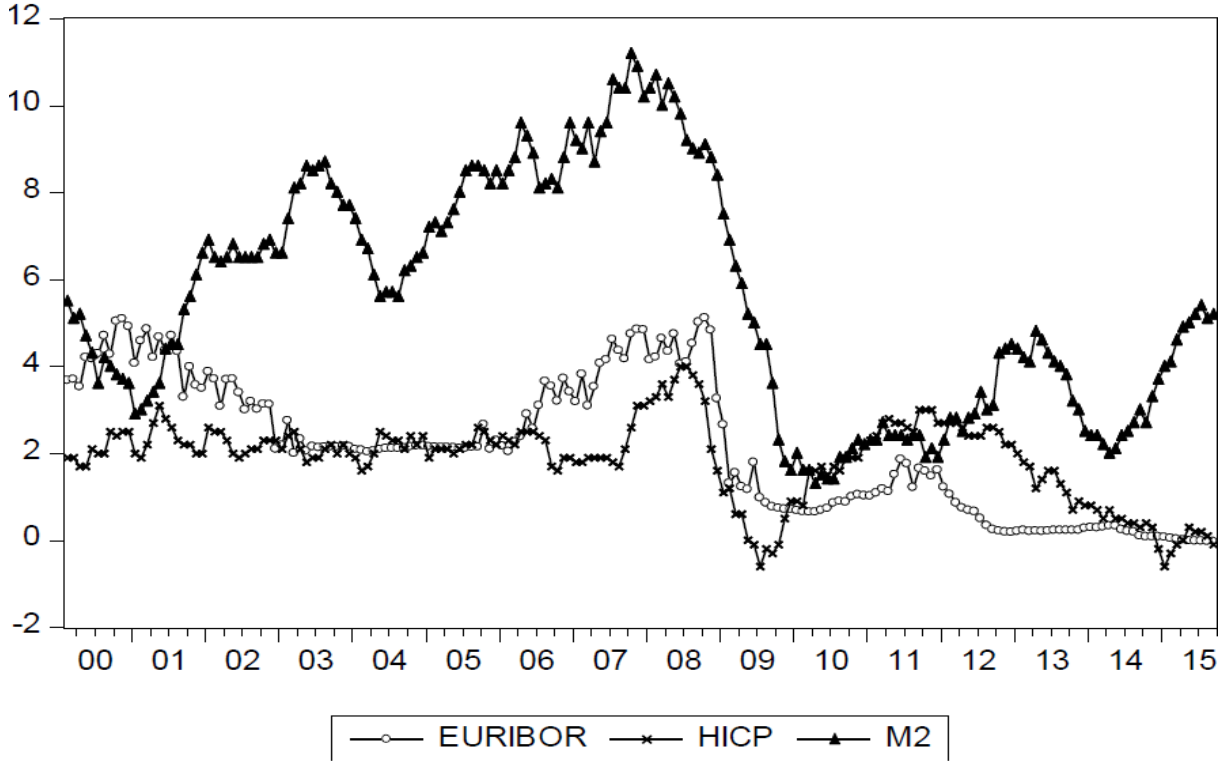
Industrial production refers to the output of industrial establishments and covers sectors such as mining, manufacturing, electricity, gas and steam and air-conditioning. This indicator is measured in an index based on a reference period that expresses change in the volume of production output. Financial stress differs dramatically between the low and the high stress regimes. While shocks in the CISS do not exert any statistically significant output reactions during low-stress regimes, industrial production truly collapses during high-stress regimes. Similarly, it is only during high stress regimes that for instance a negative output shock leads to a subsequent increase in financial stress. Taken together, these mutual reaction patterns seem to confirm the idea that when hit by a sufficiently large shock an economy faces the risk of entering a vicious downward spiral with financial and economic stress reinforcing each other over time, a finding which could be explained theoretically by some financial accelerator mechanism

Figure 1: CISS for Eurozone



Source:Done by Matlab Software

Figure2: ICP - M2-INDUSTRIAL PRODUCTION INDEX-M2-RESIDENTIAL PROPERTY PRICE



Source: ECB Statistical Data Warehouse

Section 2: Empirical Illustration of Bayesian VAR Methods

To illustrate Bayesian VAR methods using some of the priors and methods described above, we use a monthly Eurozone data set on: Systemic risk "CISS",**3** month Euribor interest rate "MEURIBOR", *Index* of Consumer Prices "ICP ", Money supply "M2", Industrial production index "INP", And Residential property price "RPP".
Thus y_t= (CISS, MEURIBOR, ICP, M2, INP, RPP)', the sample runs from 2000M1 to 2018M3.
To illustrate Bayesian VAR analysis using this data, we work with an unrestricted VAR with an intercept and four lags of all variables included in every equation and consider the following six priors:

- **Noninformative** :Noninformative version of natural conjugate prior[the equations :

$\alpha|\sum \sim N(\underline{\alpha},\sum\otimes\underline{V})$ and $\sum^{-1}\sim$W($\underline{S^{-1}}$,$\underline{v}$)] ,where $\underline{\alpha}$, $\underline{V}$, $\underline{v}$:Are prior hyparameters ,with

$\underline{\alpha} = 0_{KM\times1}$, $\underline{V} = 100I_{K\times K}$ And $\underline{v} = 0$,And $\underline{S}$=$0_{M\times M}$

- **Natural conjugate /informative natural conjugate prior** :with subjectively chosen prior hyparameters [[the equations : $\alpha|\sum \sim N(\underline{\alpha},\sum\otimes\underline{V})$ and $\sum^{-1}\sim$W($\underline{S^{-1}}$,$\underline{v}$)],with

$\underline{\alpha} = 0_{KM\times1}$, $\underline{V} = 10I_K$ And $\underline{v} = M + 1$,And $\underline{S^{-1}}$=I_M

- **Minnesota prior:[**equations :$\alpha\sim N(\underline{\alpha_{Mn}}, \underline{V_{Mn}})$ and

$$\underline{V_{i,jj}} = \begin{cases} \frac{\alpha_1}{r^2} & \text{For coefficients on own lag r for } r = 1, \ldots\ldots p \\ \frac{\alpha_2}{r^2}\frac{\sigma_{ii}}{\sigma_{jj}} & \text{For coefficients on own lag r of variables } j \neq i \text{ for } r = 1, \ldots\ldots p \\ \underline{\alpha_3}\,\sigma_{ii} & \text{For coefficients on exogenous variables} \end{cases}$$

- **Independent Normal-Wishart :Independent Normal Wishart prior:**

With: subjectively chosen prior hyperparameters [Equations :$\beta\sim N(\underline{\beta}, \underline{V_\beta})$

And $\sum^{-1}\sim W(\underline{S^{-1}}$,$\underline{v}$)] , With : $\underline{\beta}, = 0_{KM\times1}$, $\underline{V_\beta}$=$10I_{KM}$, $\underline{v}$=M+1 And $\underline{S^{-1}}$=I_M

- SSVS-VAR Prior: for VAR coefficients (with default semi-automatic approach prior with c_0=0.1 And $c_1 = 10$) and wishart prior for $\sum^{-1}$

[Equation: $\sum^{-1} \sim W(\underline{S^{-1}}, \underline{v})$],with $\underline{v}$=M+1 And $\underline{S^{-1}}$=I_M

- SSVS:SSVS on both VAR coefficients and error covariance (default semi-automatic approach)

For the three priors: diffuse, independent normal wishart and SSVS-wishart analytical posterior and predictive results are available. For the last three, posterior and predictive simulation is used on the Matlab code (Appendix1). The results below are based on 500 MCMC draws, for which the first 20 are discarded as burn-in draws. For impulse responses (which are nonlinear functions of the VAR coefficients and $\sum$), posterior simulation methods are used for all six priors.

- Considered a structural VARs ,often written as:

$$C_0 y_t = c_0 + \sum_{j=1}^{p} C_j y_{t-j} + u_t$$

Where u_t is i.i.d .N(0,I), Often appropriate identifying restrictions will provide a one-to-one mapping from the parameters of the reduced form VAR in (1) to the structural VAR. In this case, Bayesian inference can be done by using posterior simulation methods in the reduced form VAR and transforming each draw into a draw from the structural VAR.

With regards to impulse responses, they are identified by assuming C0 in the equation above is lower triangular and the dependent variables are ordered as: ICP, M2 and MEURIBOR. This is a standard identifying assumption used, among many authors, as by Primiceri (2005). It allows for the interpretation of the interest rate shock as a monetary policy shock.
Table 1 presents posterior means of all the VAR coefficients for two priors: the diffuse one and SSVS prior. Note that they are yielding similar results, although there is some evidence that SSVS is slightly shrinking the coefficients towards zero.

Table1: diffuse prior

	$CISS_t$	$MEURIBO$	ICP_t	$M2_t$	INP_t	RPP_t
Intercept	-0,3057	-0,1948	0,0887	-3,328	4,467	0,399
$CISS_{t-1}$	1,0975	0,15238	0,04099	1,6621	0,086	0,3955
$CISS_{t-2}$	-0,0204	1,624314	-0,178	-0,1459	1,727	-0,007737
$CISS_{t-3}$	-0,0109	0,8288	0,6695	0,0283	2,749	-0,03151
$CISS_{t-4}$	0,0001	-0,0473	0,03633	1,0943	-0,098	0,003387
$MEURIBOR_{t-1}$	0,0044	-0,0047	0,029077	0,0033	0,761	-0,0055
$MEURIBOR_{t-2}$	0,0114	-0,0253	0,10311	0,8418	0,471	1,0249
$MEURIBOR_{t-3}$	-0,03	-1,4498	0,7454	-4,533	-7,29	-0,1228
$MEURIBOR_{t-4}$	-0,019	-0,7015	0,1	0,9297	1,502	-0,00676
ICP_{t-1}	-0,023	-0,71151	0,059843	0,7372	2,767	-0,0115
ICP_{t-2}	-0,018	0,06099	-0,03904	-0,0667	0,461	-0,0013
ICP_{t-3}	-0,0008	-0,05228	0,049942	-0,0517	0,143	0,008974
ICP_{t-4}	0,01103	0,18502	0,227470	0,6410	0,173	-0,45132
$M2_{t-1}$	-0,1442	-0,34728	1,0332	1,2313	4,066	-0,32799
$M2_{t-2}$	0,0534	0,279	-0,2447	1,3077	-0,719	0,04025
$M2_{t-3}$	0,0573	0,39061	-0,383	1,3055	0,103	0,0868
$M2_{t-4}$	0,0125	-0,031	-0,03372	-0,0342	0,028	-0,003
INP_{t-1}	0,002	0,0005424	0,01276	0,0554	0,236	0,0020587
INP_{t-2}	-0,0516	-0,008963	0,005765	0,3608	0,275	0,5576456
INP_{t-3}	-0,027929	-0,3249	0,35641	0,2585	3,037	0,1306
INP_{t-4}	-0,0019	0,0146	0,02516	0,5959	0,297	-0,04288
RPP_{t-1}	0,001095	0,02894	0,014312	0,7921	0,358	-0,05336
RPP_{t-2}	0,005	0,06002	0,008151	-0,0608	0,331	0,0057
RPP_{t-3}	-0,0061	-0,03029	0,020902	-0,0051	0,186	-0,00484
RPP_{t-4}	0,03273	-0,061864	0,008	-0,5305	-0,583	-0,13486

Table2:SSVS-VAR prior

	$CISS_t$	$MEURIBO$	ICP_t	$M2_t$	INP_t	RPP_t
Intercept	0,043	0,075	-0,040	0,007	7,111	0,011
$CISS_{t-1}$	0,965	-0,006	0,301	-0,088	0,009	0,002
$CISS_{t-2}$	-0,005	1,507	-0,016	-0,033	2,271	-0,013
$CISS_{t-3}$	0,002	0,603	0,929	0,007	3,152	0,010
$CISS_{t-4}$	-0,001	0,004	-0,003	0,983	0,010	-0,001
$MEURIBOR_{t-1}$	0,000	0,000	0,024	0,001	0,732	0,000
$MEURIBOR_{t-2}$	-0,001	-0,005	-0,022	-0,035	0,063	0,982
$MEURIBOR_{t-3}$	0,016	-0,162	0,088	-0,212	0,345	-0,003
$MEURIBOR_{t-4}$	0,008	-0,573	-0,032	0,030	2,701	-0,012
ICP_{t-1}	0,000	-0,613	-0,066	0,142	3,497	0,004
ICP_{t-2}	0,000	0,000	-0,004	0,007	0,001	-0,004
ICP_{t-3}	0,000	-0,004	0,004	-0,007	0,252	0,000
ICP_{t-4}	0,000	0,001	-0,018	-0,020	0,020	-0,202
$M2_{t-1}$	-0,026	0,006	0,122	-0,017	0,148	0,027
$M2_{t-2}$	-0,002	0,006	0,033	-0,014	0,086	0,006
$M2_{t-3}$	-0,002	0,034	-0,022	-0,009	0,027	-0,003
$M2_{t-4}$	0,000	0,006	0,000	-0,011	0,053	-0,006
INP_{t-1}	0,000	0,001	-0,002	-0,003	0,009	-0,001
INP_{t-2}	0,002	-0,009	-0,006	0,046	0,069	0,219
INP_{t-3}	-0,004	0,082	-0,119	-1,310	0,018	-0,059
INP_{t-4}	-0,002	0,005	0,000	-0,003	0,037	0,014
RPP_{t-1}	0,003	0,033	-0,012	-0,028	-0,131	-0,003
RPP_{t-2}	0,000	-0,001	-0,011	0,001	-0,031	0,018
RPP_{t-3}	0,000	0,001	-0,003	0,004	0,002	0,000
RPP_{t-4}	-0,001	0,012	0,025	0,016	-0,086	0,002

Remember that SSVS allows to the calculation of $\Pr(\gamma_j = 1)$for each VAR coefficient and such posterior inclusion probabilities can be used either in model averaging or as an informal measure of whether an explanatory variable should be included or not.
We used SSVS to select a single model would restrict most of the remaining VAR coefficients to be zero.

- **Predictive means and standard deviations**

Predictive means and standard deviations are similar for all six priors, although it can be seen that the predictive standard deviations

Table3: Predictive mean of y_{T+1} and standard deviation

PRIOR	$CISS_{T+1}$	$MEURIBOR_{T+1}$	ICP_{T+1}	$M2_{T+1}$	INP_{T+1}	RPP_{T+1}
Diffuse	0,07686391	-1,63148423	1,32863673	5,55237355	107,004387	103,145637
	0,03054688	0,25181507	0,24700817	0,37750441	0,96466399	0,0896764
Minnesota	0,07366393	-1,62647197	1,32194081	5,51719983	106,946783	103,141391
	0,02974996	0,262286	0,25755805	0,37635611	1,00763047	0,0856771
normal_ wishart	0,0735018	-1,62329785	1,32114589	5,506993	107,151848	103,14726
	0,07904831	0,24610295	0,23917397	0,3594341	0,91586937	0,11341122
Ind-normal_wishart	0,07471432	-1,61946295	1,33155454	5,43330054	107,54948	103,153256
	0,08143915	0,25410627	0,24754312	0,37514977	0,9856041	0,11643073
SSVS - VAR	0,0640689	-1,61384035	1,30834938	5,44809277	106,963606	103,147035
	0,07685496	0,25629408	0,25106325	0,36740443	0,95480258	0,11160805
SSVS	0,06976204	-1,59107371	1,27776525	5,4318657	107,038746	103,149822
	0,02930882	0,25085965	0,24260012	0,36834462	0,95525003	0,08619316
True value, Y_{T+1}	0,0537	-1,4285	1,1	4,9	105,7	103,14

As it was mentioned previously, our methodological approach allows the coefficients to vary over time, so we can investigate the effect of monetary policy on the systemic risk in different periods. First, we consider systemic risk response during June 2007 which can be characterized as the build-up phase before the financial crisis. We would expect this to be the highest response to monetary policy

Figure3: Impulse response of Diffuse prior (The solid line represents the posterior median responses; the dashed lines are the 0.1 and 0.9 quantiles (based on 500 simulations with 20 burn-in draws). Numbers on the horizontal axis denote months.)

Source: Done by Matlab

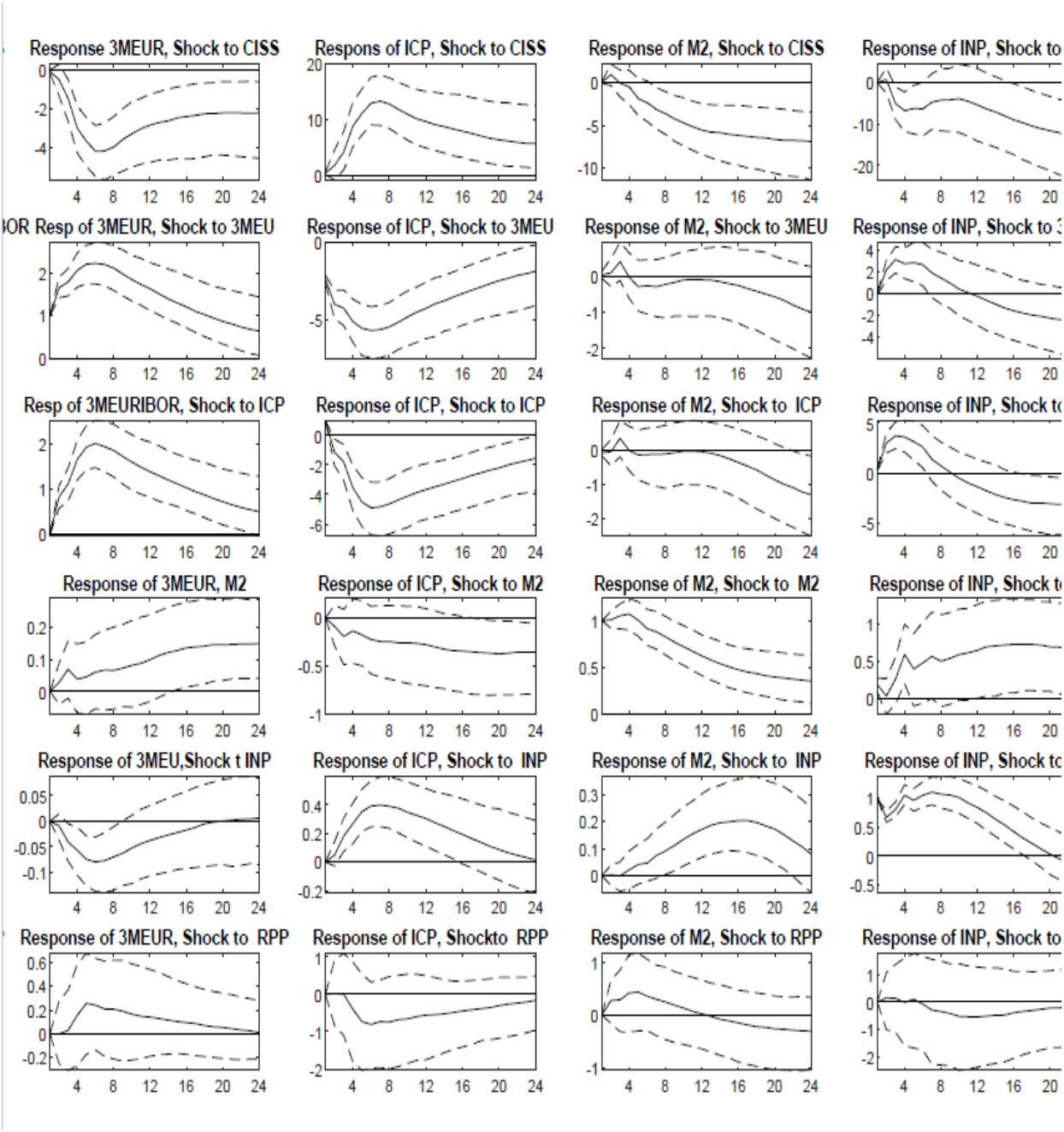


Figure4: Impulse response of SSVS prior (Source: Done by Matlab)

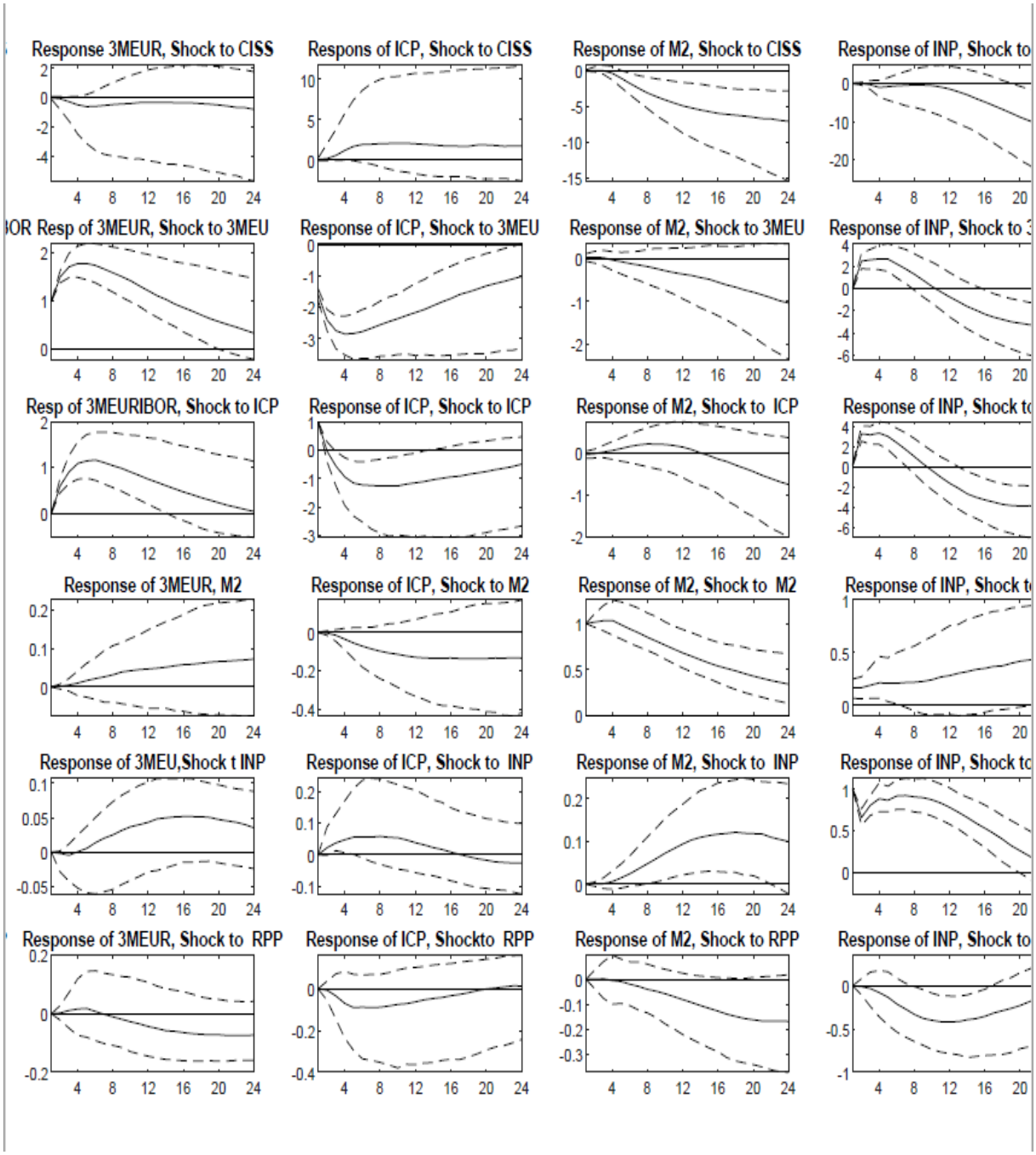


Figure5: Posterior Predictive (Source: Done by Matlab)

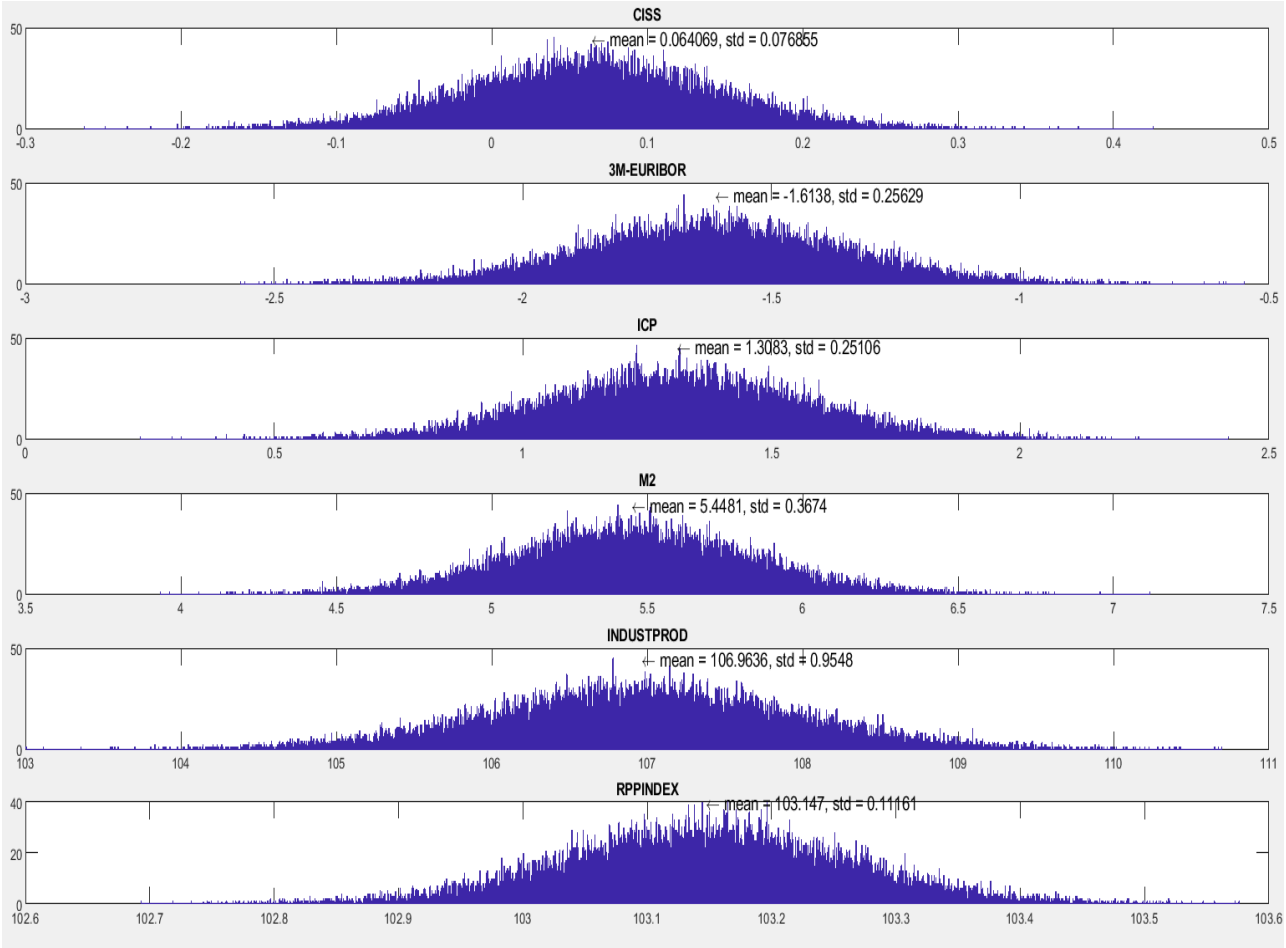


Figure 5 plots posterior means of the time-varying deviation in CISS, ICP, 3M-EURIBOR and M2, INP And RPP equation. First graph presents the stochastic volatility of CISS indicator driven by monetary policy. We can see that in the build-up phase in systemic risk we can considered as the during corresponding from 2005 to 2007 where the monetary policy volatility played an important role in systemic risk. Clearly, the initially free monetary policy period and cheap loans has fed the mortgage crisis resulted in the widespread financial crisis. The variance declines after the ECB decided to drop official interest rates to near-zero values[Negative scale]. ICP graph shows variance in the inflation equation where we can expect strong effects of the taken monetary policy, since the primary goal of ECB is to maintain price stability. Third and fourth graph outlines the variance in monetary policy variables. It can be The period from 2005 to 2009 exhibits a substantially higher variance of monetary policy shocks. However, after the crisis volatility declines. We can observe that RPP knew some peaks before 2008 crisis ,the INP was also significant so we can say that these two variables behave commonly, when INP and RPP reach high level which refer tohousing market boom which implies a high growth for economy which pushes the systemic risk rate to decrease .

Section 3: Forecasting

Using the same monthly data and the same six variables used above with keeping the same number of lag VAR(4).It can also be seen that usually (but not always), the larger VARs forecast better than the small VAR. If we look only at the small VARs, the SSVS prior

often leads to the best forecast performance. Mean square forecast error, MSFE, is the most common measure of forecast comparison. It is defned as:

$$MSFE = \frac{\sum_{\tau=\tau_0}^{T-h} \left[y_{i,\tau+h}^{o} - E\left(y_{i,\tau+h}|Data_\tau\right)\right]^2}{T-h-\tau_0+1}.$$

Table 4, MSFE is presented as a proportion of the MSFE produced by random forecasts. MSFE only uses the point forecasts and ignores the rest of the predictive distribution. Predictive likelihoods evaluate the forecasting performance of the entire predictive density. The predictive likelihood is the predictive density for $y_{i,\tau+h}$ evaluated at the actual outcome $y_{i,\tau+h}^{0}$. The sum of log predictive likelihoods can be used for forecast evaluation:

$$\sum_{\tau=\tau_0}^{T-h} \log\left[p\left(y_{i,\tau+h} = y_{i,\tau+h}^{o}|Data_\tau\right)\right]$$

Table 4 presents MSFEs and sums of log predictive likelihoods for our three main variables of interest for forecast horizons one quarter and one year in the future. All of the Bayesian VARs forecast substantially better than a random walk for all variables. Here we combine the Minnesota prior with the SSVS prior in order surmount the problem of lack of shrinkage which lead sometimes to a worsening of forecast performance. Sometimes log predictive likelihoods (the preferred Bayesian forecast metric) can paint a different picture than MSFEs. Sometimes the same the forecast horizon is one month

Table 4: MSFEs

Variables	CISS	3M-EUR	ICP	M2	INP	RPP
Minnesota Prior	0,00039856	0,0391929	0,04925772	0,38093563	1,55446812	1,94E-06
SSVS Prior	0,00010751	0,03435104	0,04340946	0,30040568	1,59669923	4,95E-05

Log predictive likelihoods (Minnesota Prior) = -1, 8732

Log predictive likelihoods (SSVS) = 0, 03250592

Conclusion

The findings of our analysis can be summarized as follows: we found that a restrictive monetary policy does not necessarily reduce the level of systemic risk, which applies to both the pre-crisis and post-crisis periods. On the contrary, the lowering of interest rates increased the systemic risk measured by CISS with a lag of up to 3 months. Hence, a 1% interest rate increase causes the amount of capital needed by a financial firm in the event of a crisis to increase up to 0,25%. The increase in systemic risk due to lower interest rates is persistent during the whole studied period. The ECB policy on managing interest rates reduced inflation before and during the crisis, but has zero effect on inflation in near deflation times (after the crisis). We also found that the recent monetary expansion in the form of quantitative easing did not raise inflation, but increased the level of systemic risk. Also therefore; excessive money supply does not help finance the real sector of the economy, but presumably encourages speculation. Our analysis suggests that unconventional monetary policy brings unwanted results and further escalates financial instability in Eurozone countries.Also when INP and RPP reach high level which refers to housing market boom which implies a high growth for economy which pushes the systemic risk rate to decrease.

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APPENDICES

Appendix A : Code Matlab

```
% BVAR_FULL.m
% This code replicates the results from the 1st empirical illustration
% in Koop and Korobilis (2009).
%
% You can chose 6 different priors. For some priors, analytical results are
% available, so Monte Carlo Integration is used. For other priors, you need
% to use the Gibbs sampler. For Gibbs sampler models I take a number of
% 'burn-in draws', so that I keep only the draws which have converged.
%
% The specification of the prior hyperparmeters are in the file
% prior_hyper.m. See there for details.
%
% The convention used here is that ALPHA is the K x M matrix of VAR coefficients,
% alpha is the KM x 1 column vector of vectorized VAR coefficients, i.e.
% alpha = vec(ALPHA), and SIGMA is the M x M VAR covariance matrix.
%-----------------------------------------------------------------------
% Bayesian estimation, prediction and impulse response analysis in VAR
% models using posterior simulation. Dependent on your choice of forecasting,
% the VAR model is:
%
% In this code we provide direct (as opposed to iterated) forecasts
% Direct h-step ahead foreacsts:
%     Y(t+h) = A0 + Y(t) x A1 + ... + Y(t-p+1) x Ap + e(t+h)
%
% so that in this case there are also p lags of Y (from 0 to p-1).
%
% In any of the two cases, the model is written as:
%
%                 Y(t) = X(t) x A + e(t)
%
% where e(t) ~ N(0,SIGMA), and A summarizes all parameters. Note that we
% also use the vector a which is defined as a=vec(A).
%-----------------------------------------------------------------------
% NOTES: The code sacrifices efficiency for clarity. It follows the
%        theoretical equations in the monograph and the manual.
%
% AUTHORS: Gary Koop and Dimitris Korobilis
% CONTACT: dikorombilis@yahoo.gr
%-----------------------------------------------------------------------

clear all;
clc;
randn('seed',2); %#ok<RAND>
rand('seed',2); %#ok<RAND>

%------------------------------LOAD DATA-----------------------------------
% Load Monthly EUROZONE data on SYSTEMIC RISK(CISS),3M-EURIBOR,ICP,
M2,INDUSTRIAL PRODUCTION and RESIDENTIEL PROPERTY PRICE,
```

```
% 2000:M1 - 2018:M3
load('C:\Users\moi\Desktop\données\ydata.mat');
Yraw=ydata;
%%%DEFINE VARIABLES AND MAKE IT STATIONAIRY %%%%%
CISS = Yraw(:,1);
MEURIBOR = Yraw(: ,2);
ICP = Yraw(:,3);
M2 = Yraw(:,4);
INP = Yraw(:,5);
RPP = Yraw(:,6);
INPR=diff(log(INP));
RPPR = diff(log(RPP));

%Yraw = Yraw(29:189,:);
% or Simulate data from a simple VAR Data Generating process
%[Yraw] = bvardgp();

% In any case, name the data you load 'Yraw', in order to avoid changing the
% rest of the code. Note that 'Yraw' is a matrix with T rows by M columns,
% where T is the number of time series observations (usually months or
% quarters), while M is the number of VAR dependent macro variables.

%----------------------------PRELIMINARIES--------------------------------
% Define specification of the VAR model
constant = 1;       % 1: if you desire intercepts, 0: otherwise
p = 4;              % Number of lags on dependent variables
forecasting = 1;    % 1: Compute h-step ahead predictions, 0: no prediction

repfor = 50;        % Number of times to obtain a draw from the predictive
                    % density, for each generated draw of the parameters
h = 1;              % Number of forecast periods
impulses = 1;       % 1: compute impulse responses, 0: no impulse responses
ihor = 24;          % Horizon to compute impulse responses

% Set prior for BVAR model:
prior = 5;% prior = 1 --> Diffuse ('Jeffreys') (M-C Integration)
          % prior = 2 --> Minnesota          (M-C Integration)
          % prior = 3 --> Normal-Wishart      (M-C Integration)
          % prior = 4 --> Independent Normal-Wishart     (Gibbs sampler)
          % prior = 5 --> SSVS in mean-Wishart          (Gibbs sampler)
          % prior = 6 --> SSVS in mean-SSVS in covariance (Gibbs sampler)


% Gibbs-related preliminaries
nsave = 500;        % Final number of draws to save
nburn = 20;         % Draws to discard (burn-in)
% For models using analytical results, there are no convergence issues (You
% are not adviced to change the next 3 lines)
if prior ==1 || prior == 2 || prior == 3
   nburn = 0*nburn;
end
ntot = nsave + nburn;  % Total number of draws
it_print = 20;      % Print on the screen every "it_print"-th iteration
%-------------------------DATA HANDLING----------------------------------
% Get initial dimensions of dependent variable
```

```
[Traw M] = size(Yraw);

% The model specification is different when implementing direct forecasts,
% compared to the specification when computing iterated forecasts.
if forecasting==1
   if h<=0 % Check for wrong (incompatible) user input
      error('You have set forecasting, but the forecast horizon choice is wrong')
   end
   % Now create VAR specification according to forecast method

      Y1 = Yraw(h+1:end,:);
      Y2 = Yraw(2:end-h,:);
      Traw = Traw - h - 1;

else
  Y1 = Yraw;
  Y2 = Yraw;
end

% Generate lagged Y matrix. This will be part of the X matrix
Ylag = mlag2(Y2,p); % Y is [T x M]. ylag is [T x (Mp)]

% Now define matrix X which has all the R.H.S. variables (constant, lags of
% the dependent variable and exogenous regressors/dummies).
% Note that in this example I do not include exogenous variables (other macro
% variables, dummies, or trends). You can load a file with exogenous
% variables, call them, say W, and then extend variable X1 in line 133, as:
%          X1 = [ones(Traw-p,1) Ylag(p+1:Traw,:) W(p+1:Traw,:)];
% and line 135 as:
%          X1 = [Ylag(p+1:Traw,:)  W(p+1:Traw,:)];
if constant
   X1 = [ones(Traw-p,1) Ylag(p+1:Traw,:)];
else
   X1 = Ylag(p+1:Traw,:);  %#ok<UNRCH>
end

% Get size of final matrix X
[Traw3 K] = size(X1);

% Create the block diagonal matrix Z
Z1 = kron(eye(M),X1);

% Form Y matrix accordingly
% Delete first "LAGS" rows to match the dimensions of X matrix
Y1 = Y1(p+1:Traw,:); % This is the final Y matrix used for the VAR

% Traw was the dimesnion of the initial data. T is the number of actual
% time series observations of Y and X
T = Traw - p;

%========= FORECASTING SET-UP:
% Now keep also the last "h" or 1 observations to evaluate (pseudo-)forecasts
if forecasting==1
   Y_pred = zeros(nsave*repfor,M); % Matrix to save prediction draws
   PL = zeros(nsave,1);          % Matrix to save Predictive Likelihood
```

```
    % Direct forecasts, we only need to keep the last observation for evaluation
        Y = Y1(1:end-1,:);
        X = X1(1:end-1,:);
        Z = kron(eye(M),X);
        T = T - 1;

else % if no prediction is present, keep all observations
    Y = Y1;
    X = X1;
    Z = Z1;
end

%========= IMPULSE RESPONSES SET-UP:
% Create matrices to store forecasts
if impulses == 1;
    imp_CISS = zeros(nsave,M,ihor); % impulse responses to a shock in CISS
    imp_MEURIBOR = zeros(nsave,M,ihor);  % impulse responses to a shock 3M-EURIBOR
   imp_ICP = zeros(nsave,M,ihor);  % impulse responses to a shock in INFLATION
   imp_M2 = zeros(nsave,M,ihor); % impulse responses to a shock in M2
    imp_INPR = zeros(nsave,M,ihor);  % impulse responses to a shock INDUSTPROD
   imp_RPPR = zeros(nsave,M,ihor);  % impulse responses to a shock in RPP
    bigj = zeros(M,M*p);
    bigj(1:M,1:M) = eye(M);
end

%----------------------------PRELIMINARIES-------------------------------
% First get ML estimators
A_OLS = inv(X'*X)*(X'*Y); % This is the matrix of regression coefficients
a_OLS = A_OLS(:);        % This is the vector of parameters, i.e. it holds
                         % that a_OLS = vec(A_OLS)
SSE = (Y - X*A_OLS)'*(Y - X*A_OLS);   % Sum of squared errors
SIGMA_OLS = SSE./(T-K+1);

% Initialize Bayesian posterior parameters using OLS values
alpha = a_OLS;     % This is the single draw from the posterior of alpha
ALPHA = A_OLS;     % This is the single draw from the posterior of ALPHA
SSE_Gibbs = SSE;   % This is the SSE based on each draw of ALPHA
SIGMA = SIGMA_OLS; % This is the single draw from the posterior of SIGMA
IXY =  kron(eye(M),(X'*Y));


 %%%Storage space for posterior draws
alpha_draws = zeros(nsave,K*M);   % save draws of alpha
ALPHA_draws = zeros(nsave,K,M);   % save draws of alpha
SIGMA_draws = zeros(nsave,M,M);   % save draws of ALPHA

%-----------------Prior hyperparameters for bvar model
% load file which sets hyperparameters for chosen prior
prior_hyper;
%-------------------- Prior specification ends here

%========================== Start Sampling ================================
%=====================================================================
===
```

```
tic;
disp('Number of iterations');
for irep = 1:ntot  %Start the Gibbs "loop"
   if mod(irep,it_print) == 0 % print iterations
      disp(irep);
      toc;
   end

   %--------- Draw ALPHA and SIGMA with Diffuse Prior
   if prior == 1
      % Posterior of alpha|SIGMA,Data ~ Normal
      V_post = kron(SIGMA,inv(X'*X));
      alpha = a_OLS + chol(V_post)'*randn(K*M,1);% Draw alpha
      ALPHA = reshape(alpha,K,M); % Create draw of ALPHA

      % Posterior of SIGMA|Data ~ iW(SSE_Gibbs,T-K)
      SIGMA = inv(wish(inv(SSE_Gibbs),T-K));% Draw SIGMA

   %--------- Draw ALPHA and SIGMA with Minnesota Prior
   elseif prior == 2
      %Draw ALPHA
      for i = 1:M
         V_post = inv( inv(V_prior((i-1)*K+1:i*K,(i-1)*K+1:i*K)) + inv(SIGMA(i,i))*X'*X );
         a_post   =   V_post*(inv(V_prior((i-1)*K+1:i*K,(i-1)*K+1:i*K))*a_prior((i-1)*K+1:i*K,1)   +
inv(SIGMA(i,i))*X'*Y(:,i));
         alpha((i-1)*K+1:i*K,1) = a_post + chol(V_post)'*randn(K,1); % Draw alpha
      end
      ALPHA = reshape(alpha,K,M); % Create draw in terms of ALPHA

      % SIGMA in this case is a known matrix, whose form is decided in
      % the prior (see prior_hyper.m)

   %--------- Draw ALPHA and SIGMA with Normal-Wishart Prior
   elseif prior == 3
      % ******Get all the required quantities for the posteriors
      V_post = inv( inv(V_prior) + X'*X );
      A_post = V_post*(inv(V_prior)*A_prior + X'*X*A_OLS);
      a_post = A_post(:);

      S_post   =   SSE   +   S_prior   +   A_OLS'*X'*X*A_OLS   +   A_prior'*inv(V_prior)*A_prior   -
A_post'*(inv(V_prior) + X'*X)*A_post;
      v_post = T + v_prior;

      % This is the covariance for the posterior density of alpha
      COV = kron(SIGMA,V_post);

      % Posterior of alpha|SIGMA,Data ~ Normal
      alpha = a_post + chol(COV)'*randn(K*M,1);  % Draw alpha
      ALPHA = reshape(alpha,K,M); % Draw of ALPHA

      % Posterior of SIGMA|ALPHA,Data ~ iW(inv(S_post),v_post)
      SIGMA = inv(wish(inv(S_post),v_post));% Draw SIGMA

   %--------- Draw ALPHA and SIGMA with Independent Normal-Wishart Prior
   elseif prior == 4
```

```
    VARIANCE = kron(inv(SIGMA),eye(T));
    V_post = inv(V_prior + Z'*VARIANCE*Z);
    a_post = V_post*(V_prior*a_prior + Z'*VARIANCE*Y(:));
    alpha = a_post + chol(V_post)'*randn(n,1); % Draw of alpha

    ALPHA = reshape(alpha,K,M); % Draw of ALPHA

    % Posterior of SIGMA|ALPHA,Data ~ iW(inv(S_post),v_post)
    v_post = T + v_prior;
    S_post = S_prior + (Y - X*ALPHA)'*(Y - X*ALPHA);
    SIGMA = inv(wish(inv(S_post),v_post));% Draw SIGMA

%--------- Draw ALPHA and SIGMA using SSVS prior
elseif prior == 5 || prior == 6
    % Draw SIGMA
    if prior == 5 % Wishart
        % Posterior of SIGMA|ALPHA,Data ~ iW(inv(S_post),v_post)
        v_post = T + v_prior;
        S_post = inv_S_prior + (Y - X*ALPHA)'*(Y - X*ALPHA);
        SIGMA = inv(wish(inv(S_post),v_post));% Draw SIGMA
    elseif prior == 6 % SSVS
        % Draw psi|alpha,gamma,omega,DATA from the GAMMA dist.
        % Get S_[j] - upper-left [j x j] submatrices of SSE
        % The following loop creates a cell array with elements S_1,
        % S_2,...,S_j with respective dimensions 1x1, 2x2,...,jxj
        S=cell(1,M);
        for kk_2 = 1:M
            S{kk_2} = SSE_Gibbs(1:kk_2,1:kk_2);
        end
        % Set also SSE =(s_[i,j]) & get vectors s_[j]=(s_[1,j] , ... , s_[j-1,j])
        s=cell(1,M-1);
        for kk_3 = 2:M
            s{kk_3 - 1} = SSE_Gibbs(1:(kk_3 - 1),kk_3);
        end
        % Parameters for Heta|omega ~ N_[j-1](0,D_[j]*R_[j]*D_[j]), see eq. (15)
        % Create and update h_[j] matrix
        % If omega_[ij] = 0 => h_[ij] = kappa0, else...
        hh=cell(1,M-1);
        for kk_4 = 1:M-1
            omeg = cell2mat(omega(kk_4));
            het = cell2mat(hh(kk_4));
            for kkk = 1:size(omeg,1)
                if omeg(kkk,1) == 0
                    het(kkk,1) = kappa_0;
                else
                    het(kkk,1) = kappa_1;
                end
            end
            hh{kk_4} = het;
        end
        % D_j = diag(hh_[1j],...,hh_[j-1,j])
        D_j=cell(1,M-1);
        for kk_5 = 1:M-1
            D_j{kk_5} = diag(cell2mat(hh(kk_5)));
        end
```

```
% Now create covariance matrix D_[j]*R_[j]*D_[j], see eq. (15)
DD_j=cell(1,M-1);
for kk_6 = 1:M-1
   DD = cell2mat(D_j(kk_6));
   DD_j{kk_6} = (DD*DD);
end
% Create B_[i] matrix
B=cell(1,M);
for rr = 1:M
   if rr == 1
      B{rr} = b_i + 0.5*(SSE(rr,rr));
   elseif rr > 1
      s_i = cell2mat(s(rr-1));
      S_i = cell2mat(S(rr-1));
      DiDi = cell2mat(DD_j(rr-1));
      B{rr} = b_i + 0.5*(SSE_Gibbs(rr,rr) - s_i'*inv(S_i + inv(DiDi))*s_i);
   end
end
% Now get B_i from cell array B, and generate (psi_[ii])^2
B_i = cell2mat(B);
psi_ii_sq = zeros(M,1);
for kk_7 = 1:M
   psi_ii_sq(kk_7,1) = gamm_rnd(1,1,(a_i + 0.5*T),B_i(1,kk_7));
end

% Draw eta|psi,phi,gamma,omega,DATA from the [j-1]-variate
% NORMAL dist.
eta = cell(1,M-1);
for kk_8 = 1:M-1
   s_i = cell2mat(s(kk_8));
   S_i = cell2mat(S(kk_8));
   DiDi = cell2mat(DD_j(kk_8));
   miu_j = - sqrt(psi_ii_sq(kk_8+1))*(inv(S_i + inv(DiDi))*s_i);
   Delta_j = inv(S_i + inv(DiDi));

   eta{kk_8} = miu_j + chol(Delta_j)'*randn(kk_8,1);
end

% Draw omega|eta,psi,phi,gamma,omega,DATA from BERNOULLI dist.
omega_vec = []; %temporary vector to store draws of omega
for kk_9 = 1:M-1
   omeg_g = cell2mat(omega(kk_9));
   eta_g = cell2mat(eta(kk_9));
   for nn = 1:size(omeg_g)  % u_[ij1], u_[ij2], see eqs. (32 - 33)
      u_ij1 = (1./kappa_0)*exp(-0.5*((eta_g(nn))^2)./((kappa_0)^2))*q_ij;
      u_ij2 = (1./kappa_1)*exp(-0.5*((eta_g(nn))^2)./((kappa_1)^2))*(1-q_ij);
      ost = u_ij1./(u_ij1 + u_ij2);
      omeg_g(nn,1) = bernoullirnd(ost);
      omega_vec = [omega_vec ; omeg_g(nn,1)]; %#ok<AGROW>
   end
   omega{kk_9} = omeg_g; %#ok<AGROW>
end

% Create PSI matrix from individual elements of "psi_ii_sq" and "eta"
PSI_ALL = zeros(M,M);
```

```
        for nn_1 = 1:M  % first diagonal elements
            PSI_ALL(nn_1,nn_1) = sqrt(psi_ii_sq(nn_1,1));
        end
        for nn_2 = 1:M-1 % Now non-diagonal elements
            eta_gg = cell2mat(eta(nn_2));
            for nnn = 1:size(eta_gg,1)
                PSI_ALL(nnn,nn_2+1) = eta_gg(nnn);
            end
        end
        % Create SIGMA
        SIGMA = inv(PSI_ALL*PSI_ALL');
    end % END DRAWING SIGMA

    % Draw alpha
    % Hyperparameters for alpha|gamma ~ N_[m](0,D*D)
    h_i = zeros(n,1);   % h_i is tau_0 if gamma=0 and tau_1 if gamma=1
    for nn_3 = 1:n
        if gammas(nn_3,1) == 0
            h_i(nn_3,1) = tau_0(nn_3);
        elseif gammas(nn_3,1) == 1
            h_i(nn_3,1) = tau_1(nn_3);
        end
    end
    D = diag(h_i'*eye(n)); % Create D. Here D=diag(h_i) will also do
    DD = D*D;   % Prior covariance matrix for Phi_m
    isig=inv(SIGMA);
    psi_xx = kron(inv(SIGMA),(X'*X));
    V_post = inv(psi_xx + inv(DD));
%       a_post = V_post*((psi_xx)*a_OLS + (inv(DD))*a_prior);

     visig=isig(:);
    a_post = V_post*(IXY*visig + inv(DD)*a_prior);
    alpha = a_post + chol(V_post)'*randn(n,1); % Draw alpha

    alpha = a_post + chol(V_post)'*randn(n,1); % Draw alpha

    ALPHA = reshape(alpha,K,M); % Draw of ALPHA

    % Draw gamma|phi,psi,eta,omega,DATA from BERNOULLI dist.
    for nn_6 = 1:n
        u_i1 = (1./tau_0(nn_6))*exp(-0.5*(alpha(nn_6)./(tau_0(nn_6)))^2)*p_i;
        u_i2 = (1./tau_1(nn_6))*exp(-0.5*(alpha(nn_6)./(tau_1(nn_6)))^2)*(1-p_i);
        gst = u_i1./(u_i1 + u_i2);
        gammas(nn_6,1) = bernoullirnd(gst); %#ok<AGROW>
    end

    % Save new Sum of Squared Errors (SSE) based on draw of ALPHA
    SSE_Gibbs = (Y - X*ALPHA)'*(Y - X*ALPHA);

end
% =============Estimation ends here



% ****************************|Predictions, Responses, etc|****************************
```

```
if irep > nburn
   %=========FORECASTING:
   if forecasting==1

         Y_temp = zeros(repfor,M);
         % compute 'repfor' predictions for each draw of ALPHA and SIGMA
         for ii = 1:repfor
            X_fore = [1 Y(T,:) X(T,2:M*(p-1)+1)];
            % Forecast of T+1 conditional on data at time T
            Y_temp(ii,:) = X_fore*ALPHA + randn(1,M)*chol(SIGMA);
         end
         % Matrix of predictions
         Y_pred(((irep-nburn)-1)*repfor+1:(irep-nburn)*repfor,:) = Y_temp;
         % Predictive likelihood
         PL(irep-nburn,:) = mvnpdf(Y1(T+1,:),X(T,:)*ALPHA,SIGMA);
         if PL(irep-nburn,:) == 0
            PL(irep-nburn,:) = 1;
         end

   end % end forecasting
   %=========Forecasting ends here

   %=========IMPULSE RESPONSES:
   if impulses==1
      % ------------Identification code I:
      Bv = zeros(M,M,p);
      for i_1=1:p
         Bv(:,:,i_1) = ALPHA(1+((i_1-1)*M + 1):i_1*M+1,:);
      end

      % st dev matrix for structural VAR
      shock = chol(SIGMA)';
      d = diag(diag(shock));
      shock = inv(d)*shock;

      [responses]=impulse(Bv,shock,ihor);

      % Restrict to policy shocks
      responses1 = squeeze(responses(:,1,:));
      responses2 = squeeze(responses(:,2,:));
      responses3 = squeeze(responses(:,3,:));
      responses4 = squeeze(responses(:,4,:));
      responses5 = squeeze(responses(:,5,:));
      responses6 = squeeze(responses(:,6,:));

      imp_CISS(irep-nburn,:,:) = responses1;
      imp_MEURIBOR(irep-nburn,:,:) = responses2;
      imp_ICP(irep-nburn,:,:) = responses3;
      imp_M2(irep-nburn,:,:) = responses4;
      imp_INPR(irep-nburn,:,:) = responses5;
      imp_RPPR(irep-nburn,:,:) = responses6;


   end
```

```
        %----- Save draws of the parameters
        alpha_draws(irep-nburn,:) = alpha;
        ALPHA_draws(irep-nburn,:,:) = ALPHA;
        SIGMA_draws(irep-nburn,:,:) = SIGMA;
        if prior == 5 || prior == 6
            gamma_draws(irep-nburn,:) = gammas; %#ok<AGROW>
            if prior == 6
                omega_draws(irep-nburn,:) = omega_vec; %#ok<AGROW>
            end
        end

    end % end saving results

end %end the main Gibbs for loop
%====================== End Sampling Posteriors ==========================

%Posterior mean of parameters:
ALPHA_mean = squeeze(mean(ALPHA_draws,1)); %posterior mean of ALPHA
SIGMA_mean = squeeze(mean(SIGMA_draws,1)); %posterior mean of SIGMA

%Posterior standard deviations of parameters:
ALPHA_std = squeeze(std(ALPHA_draws,1)); %posterior std of ALPHA
SIGMA_std = squeeze(std(SIGMA_draws,1)); %posterior std of SIGMA

%or you can use 'ALPHA_COV = cov(alpha_draws,1);' to get the full
%covariance matrix of the posterior of alpha (of dimensions [KM x KM] )

if prior == 5 || prior == 6
    % Find average of restriction indices Gamma
    gammas = mean(gamma_draws,1);
    gammas_mat = reshape(gammas,K,M);
    if prior == 6
        % Find average of restriction indices Omega
        omega = mean(omega_draws,1)';
        omega_mat = zeros(M,M);
        for nn_5 = 1:M-1
            ggg = omega(((nn_5-1)*(nn_5)/2 + 1):(nn_5*(nn_5+1)/2),:);
            omega_mat(1:size(ggg,1),nn_5+1) = ggg;
        end
    end
end


% mean prediction and log predictive likelihood
if forecasting == 1
    Y_pred_mean = mean(Y_pred,1); % mean prediction
    Y_pred_std = std(Y_pred,1);   % std prediction
    log_PL = mean((log(PL)),1);

    %This are the true values of Y at T+h:

        true_value = Y1(T+1,:);

    %(subsequently you can easily also get MSFE and MAFE)
```

```
    %======PLOT posterior predictive
    figure
    bars = 3000;
    subplot(6,1,1)
    hist(Y_pred(:,1),bars);
    title('CISS')
    text(Y_pred_mean(:,1),max(hist(Y_pred(:,1),bars)),['\leftarrow mean = '...
        num2str(Y_pred_mean(:,1)) ', std = ' num2str(Y_pred_std(:,1))],...
        'HorizontalAlignment','left')
    subplot(6,1,2)
    hist(Y_pred(:,2),bars);
    title('3M-EURIBOR')
    text(Y_pred_mean(:,2),max(hist(Y_pred(:,2),bars)),['\leftarrow mean = '...
        num2str(Y_pred_mean(:,2)) ', std = ' num2str(Y_pred_std(:,2))],...
        'HorizontalAlignment','left')
    subplot(6,1,3)
    hist(Y_pred(:,3),bars);
    title('ICP')
    text(Y_pred_mean(:,3),max(hist(Y_pred(:,3),bars)),['\leftarrow mean = '...
        num2str(Y_pred_mean(:,3)) ', std = ' num2str(Y_pred_std(:,3))],...
        'HorizontalAlignment','left')
 subplot(6,1,4)
    hist(Y_pred(:,4),bars);
    title('M2')
    text(Y_pred_mean(:,4),max(hist(Y_pred(:,4),bars)),['\leftarrow mean = '...
        num2str(Y_pred_mean(:,4)) ', std = ' num2str(Y_pred_std(:,4))],...
        'HorizontalAlignment','left')
    subplot(6,1,5)
    hist(Y_pred(:,5),bars);
    title('INDUSTPROD')
    text(Y_pred_mean(:,5),max(hist(Y_pred(:,5),bars)),['\leftarrow mean = '...
        num2str(Y_pred_mean(:,5)) ', std = ' num2str(Y_pred_std(:,5))],...
        'HorizontalAlignment','left')
    subplot(6,1,6)
    hist(Y_pred(:,6),bars);
    title('RPPINDEX')
    text(Y_pred_mean(:,6),max(hist(Y_pred(:,6),bars)),['\leftarrow mean = '...
        num2str(Y_pred_mean(:,6)) ', std = ' num2str(Y_pred_std(:,6))],...
        'HorizontalAlignment','left')

end



% You can also get other quantities, like impulse responses
if impulses==1;
    % Set quantiles from the posterior density of the impulse responses
    qus = [.1, .5, .90];
    imp_resp_CISS = squeeze(quantile(imp_CISS,qus));
    imp_resp_MEURIBOR = squeeze(quantile(imp_MEURIBOR,qus));
    imp_resp_ICP = squeeze(quantile(imp_ICP,qus));
    imp_resp_M2 = squeeze(quantile(imp_M2,qus));
    imp_resp_INPR = squeeze(quantile(imp_INPR,qus));
    imp_resp_RPPR = squeeze(quantile(imp_RPPR,qus));
```

```
%======= Plot impulse responses
figure
set(0,'DefaultAxesColorOrder',[0 0 0],...
   'DefaultAxesLineStyleOrder','--|-|--')
subplot(6,6,1)
plot(squeeze(imp_resp_CISS(:,1,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of CISS, Shock to CISS')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,2)
plot(squeeze(imp_resp_MEURIBOR(:,1,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response 3MEUR, Shock to CISS')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,3)
plot(squeeze(imp_resp_ICP(:,1,:))')
hold;
plot(zeros(1,ihor),'-')
title('Respons of ICP, Shock to CISS')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,4)
plot(squeeze(imp_resp_M2(:,1,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of M2, Shock to CISS')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,5)
plot(squeeze(imp_resp_INPR(:,1,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of INP, Shock to CISS')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,6)
plot(squeeze(imp_resp_RPPR(:,1,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of RPP, Shock to CISS')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)



%%%%%%%%%%%%2

subplot(6,6,7)
plot(squeeze(imp_resp_CISS(:,2,:))')
```

```
hold;
plot(zeros(1,ihor),'-')
title('Respons of CISS,Shock to 3M-EURIBOR')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,8)
plot(squeeze(imp_resp_MEURIBOR(:,2,:))')
hold;
plot(zeros(1,ihor),'-')
title('Resp of 3MEUR, Shock to 3MEU')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,9)
plot(squeeze(imp_resp_ICP(:,2,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of ICP, Shock to 3MEU')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,10)
plot(squeeze(imp_resp_M2(:,2,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of M2, Shock to 3MEU')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,11)
plot(squeeze(imp_resp_INPR(:,2,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of INP, Shock to 3MEUR')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)

subplot(6,6,12)
plot(squeeze(imp_resp_RPPR(:,2,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of RPP, Shock to 3MEUR')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)

%%%%%%%%%%%%%%%%%%%%%%33///13
subplot(6,6,13)
plot(squeeze(imp_resp_CISS(:,3,:))')
hold;
plot(zeros(1,ihor),'-')
title('Respons CISS, Shock to  ICP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,14)
plot(squeeze(imp_resp_MEURIBOR(:,3,:))')
hold;
plot(zeros(1,ihor),'-')
title('Resp of 3MEURIBOR, Shock to ICP')
```

```
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,15)
plot(squeeze(imp_resp_ICP(:,3,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of ICP, Shock to ICP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)

subplot(6,6,16)
plot(squeeze(imp_resp_M2(:,3,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of M2, Shock to  ICP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,17)
plot(squeeze(imp_resp_INPR(:,3,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of INP, Shock to ICP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,18)
plot(squeeze(imp_resp_RPPR(:,3,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of RPP, Shock to ICP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)

%%%%%:::4%%%

subplot(6,6,19)
plot(squeeze(imp_resp_CISS(:,4,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of CISS, Shock to  M2')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,20)
plot(squeeze(imp_resp_MEURIBOR(:,4,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of 3MEUR, M2')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,21)
plot(squeeze(imp_resp_ICP(:,4,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of ICP, Shock to M2')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
```

```
subplot(6,6,22)
plot(squeeze(imp_resp_M2(:,4,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of M2, Shock to  M2')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,23)
plot(squeeze(imp_resp_INPR(:,4,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of INP, Shock to M2')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,24)
plot(squeeze(imp_resp_RPPR(:,4,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of RPP, Shock to M2')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
%%%5/////

subplot(6,6,25)
plot(squeeze(imp_resp_CISS(:,5,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of CISS, Shock to  INP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,26)
plot(squeeze(imp_resp_MEURIBOR(:,5,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of 3MEU,Shock t INP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,27)
plot(squeeze(imp_resp_ICP(:,5,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of ICP, Shock to  INP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)

subplot(6,6,28)
plot(squeeze(imp_resp_M2(:,5,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of M2, Shock to  INP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,29)
plot(squeeze(imp_resp_INPR(:,5,:))')
```

```
hold;
plot(zeros(1,ihor),'-')
title('Response of INP, Shock to  INP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,30)
plot(squeeze(imp_resp_RPPR(:,5,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of RPP, Shock to  INP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)


%%%%%%6%%%

subplot(6,6,31)
plot(squeeze(imp_resp_CISS(:,6,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of CISS, Shock to  RPP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,32)
plot(squeeze(imp_resp_MEURIBOR(:,6,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of 3MEUR, Shock to  RPP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,33)
plot(squeeze(imp_resp_ICP(:,6,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of ICP, Shockto  RPP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)

subplot(6,6,34)
plot(squeeze(imp_resp_M2(:,6,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of M2, Shock to RPP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,35)
plot(squeeze(imp_resp_INPR(:,6,:))')
hold;
plot(zeros(1,ihor),'-')
title('Response of INP, Shock to  RPP')
xlim([1 ihor])
set(gca,'XTick',0:4:ihor)
subplot(6,6,36)
plot(squeeze(imp_resp_RPPR(:,6,:))')
hold;
```

```
    plot(zeros(1,ihor),'-')
    title('Response of RPP,Shock to RPP')
    xlim([1 ihor])
    set(gca,'XTick',0:4:ihor)


end



% Clear screen and print elapsed time
clc;
toc;

% Print some directions to the user
disp('Please find the means and variances of the VAR parameters in the vectors')
disp('ALPHA_mean and ALPHA_std for the VAR regression coefficients, and ')
disp('SIGMA_mean and SIGMA_std for the VAR covariance matrix. The predictive')
disp('mean and standard deviation are in Y_pred_mean and Y_pred_std, respectively.')
disp('The log Predictive Likelihood is given by variable log_PL. The true value')
disp('of y(t+h) is given in the variable true_value. For example the mean squared')
disp('forecast error can be obtained using the command')
disp('              MSFE = (Y_pred_mean - true_value).^2')
disp('If you are using the SSVS prior, you can get the averages of the restriction')
disp('indices $\gamma$ and $\omega$. These are in the variables gammas_mat and omegas_mat')


if prior == 1; name = 'diffuse';
elseif prior == 2; name = 'minnesota';
elseif prior == 3; name = 'normal_wishart' ;
elseif prior == 4; name = 'indep_normal_wishart';
elseif prior == 5; name = 'SSVS_wishart';
elseif prior == 6; name = 'SSVS_full';
end
save(sprintf('%s_%s.mat','results',name),'-mat');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
figure
plot(MEURIBOR);
title('3MEURIBOR')
x = linspace(-18,18,219);
y = CISS;
plot(x,y)
xlim([2 18])
ylim([0 100])
```

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